Experiments designed to help the participants

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Why experiments?

- Are your programs effective in helping refugees?
  - How to find out?

- Possibility 1: Compare the outcomes of those who got the programs to others who didn’t.
  - Problem: These groups might be different for other reasons.

- Think about a doctor prescribing a medical treatment.
  - Then the patients who got the treatment might die more often.
  - But only because they were more sick to begin with!
  - “Selection problem.”
The standard way of doing experiments

> Possibility 2: Randomized experiment.
  > Create groups that are ex-ante similar, by randomly assigning participants to groups.
  > To compare apples with apples.

> Conventionally:
  > Divide the sample equally between treatments.
  > Wait until experiment is done.
  > Then compare average outcomes.
  > Use statistical tests to see whether there was any effect.
Drawbacks of conventional experiments

- This approach gets the causal effects right.
- And it gets precise estimates for every policy.
- But we need to wait a long time until we learn something.
- And we might not do the best we can for our participants.
- Think again of a medical experiment:
  - Suppose in the first few months, everybody who got the new treatment died.
  - Then you better stop the experiment!!!
Preliminary estimates for our experiment

We already have suggestive evidence that the psychological treatment performs better.
A different objective: Helping participants

- The standard approach is optimal when you want to get precise estimates of policy effects.

- But we want to instead help participants as much as possible.

- Cf. Immanuel Kant:
  “Act in such a way that you treat humanity, whether in your own person or in the person of any other, never merely as a means to an end, but always at the same time as an end.”

- This requires using the information we already have, when deciding which policy to assign people to.

- But we also want to continue learning, to do better in the future.
The exploitation / exploration tradeoff

- **Possibility 1:** Assign each participant to the policy we currently think is best.
  - Good for the current participant.
  - Problem: We might stop learning, getting stuck with a sub-optimal policy.

- **Possibility 2:** Assign participants to each policy with fixed probability over time.
  - Good for learning policy effects.
  - But not optimal for current participants.

- **Possibility 3:** Optimal strategies shift to better performing policies over time.

  - For instance *Thompson sampling*:
    - Assign each treatment with probability equal to the current probability that it is optimal.
Assignment probabilities in our experiment

As we learn that the psychological treatment does better, more participants are assigned to this treatment.
Assignment frequencies in our experiment

![Graph showing assignment frequencies over weeks of the experiment.]

- **Treatment** categories: cash, information, psychological, control.
- **Weeks:** 1 to 21.
- **Events:**
  - Start of adaptive assignment
  - Outage
  - Ramadan

The graph illustrates the frequency of assignments across these treatments and weeks, with notable spikes and changes corresponding to the specified events.
Not every policy is good for everybody.

Some things work better

- for those with more or less work experience,
- for those with more or less education,
- for women or men.

We can do better than just going with “one size fits all.”

Try to get each group what works best for them.
Combining information

- Problem: For each group and policy, we might only have very few observations.
- This means averages are unreliable estimates.
- Solution: Combining information between groups.
- Estimate effect on a group by combining
  - their own average outcomes,
  - and the average outcomes for everybody else.
- *Bayesian hierarchical models* do this optimally.
Effect heterogeneity in our experiment
THANK YOU

For all your work in making this experiment happen!